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Machine Learning for Detecting and Locating Damage in a Rotating Gear

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ABSTRACT

This paper describes a multi-disciplinary damage detection methodology that can aid in detecting and diagnosing a damage in a given structural system, not limited to the example of a rotating gear presented here. Damage detection is performed on the gear stress data corresponding to the steady state conditions. The normal and damage data are generated by a finite-difference solution of elastodynamic equations of velocity and stress in generalized coordinates[1]. The elastodynamic solution provides a knowledge of the stress distribution over the gear such as locations of stress extrema, which in turn can lead to an optimal placement of appropriate sensors over the gear to detect a potential damage. The damage detection is performed by a multi-function optimization that incorporates Tikhonov kernel regularization reinforced by an added Laplacian regularization term as used in semi-supervised machine learning. Damage is mimicked by reducing the rigidity of one of the gear teeth. Damage detection models are trained on a subset of the normal data and are then tested on the damage solution. The precision with which the damaged tooth and the extent of the damage are identified is very encouraging. The present methodology promises to lead to a significant damage detection, diagnosis and prognosis technology for structural health monitoring.

INTRODUCTION

This paper discusses how machine learning methods (Refs. 1,2) in conjunction with physics-based modeling and simulation (Refs. 3,4) can aid in determining optimal configuration for a sensor layout on a given structure for structural health monitoring as well as in structural damage detection. In conventional machine learning methodologies used in data mining to predict trends, e.g., in global climate change, training sets are often derived from some random distribution, based on which learning models are constructed. In engineering systems, where one needs to be more precise than predicting trends, deterministic domain knowledge of the particular engineering system is necessary to establish a meaningful training set for construction of such a learning model. Using this domain knowledge, a Tikhonov kernel based regularization technique along with an added Laplacian regularization term as used in semi-supervised learning (Ref. 5) can then detect and diagnose a potential damage anywhere on the structure where sensors have been placed. This is the subject of the present study.

The multi-function regularization technique is used to construct the machine learning model by training it on a subset of the normal data and then testing it on the sensor data to predict a potential damage anywhere in the domain where sensors are placed. The training set is chosen especially based on the regions of the domain where the computational models predict maximum stresses. Learning models are constructed by training them respectively on radial, tangential and shear stress fields. In all the three cases, predictions are shown to be in excellent agreement with the true solution where true solution is the finite difference solution of the elastodynamic equations governing the radial, tangential and shear stresses. Once the learning models are trained, each model is then tested on the corresponding damage stress data, and the distribution of the difference between the normal and the predicted data is then calculated all over the gear. This error distribution thus detects and quantifies the degree of damage on the damaged tooth.

A test problem is considered where a steel gear is steadily rotating at 6,000 rpm and is thus subjected to steady state radial, tangential and shear stress fields. Two cases are studied. In the first one, homogeneous material properties are considered all over the domain

[1] Provisional application for U.S. patent filed

(gear grid). In the second one, rigidity of one of the teeth is decreased in a certain fashion to reflect compromised stiffness due to, say, manufacturing variations, exposure to extreme thermal loading or an incipient crack, among others.

RESULTS

The first case considered was that of all the nineteen gear teeth having uniform material properties as those of industrial steel. The gear grid is obtained using elliptic grid generation methodology (Ref. 2)[2] and is shown below.

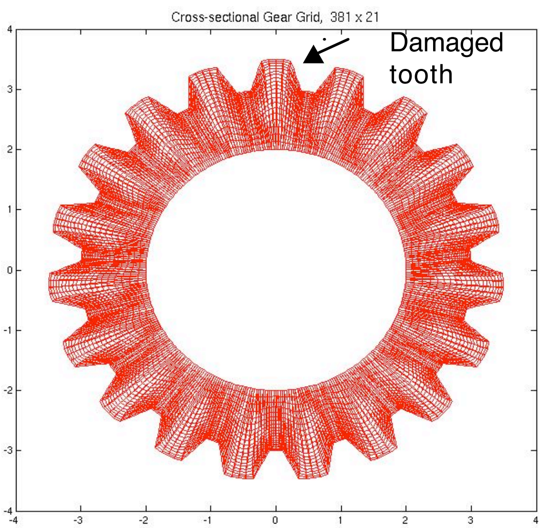
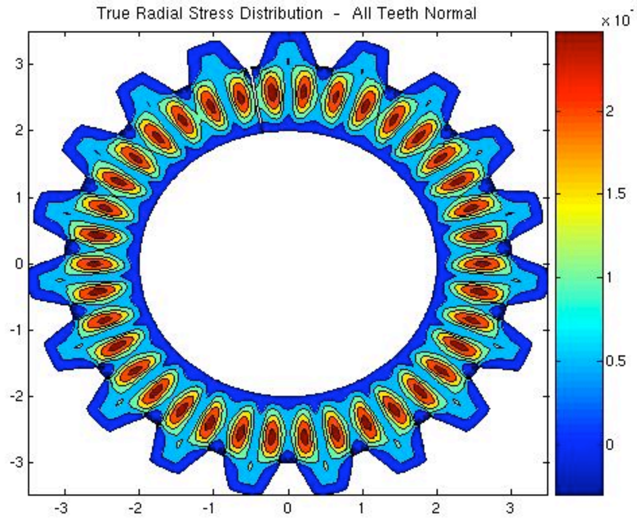


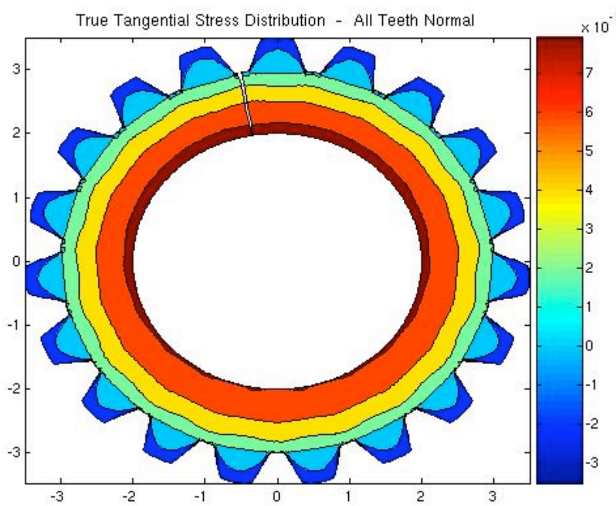
Fig. 1 A 19-tooth gear cross-section showing damaged tooth #1

The gear is impulsively rotated at 6,000 rpm. The elastodynamic partial differential equations, three for three velocity components and six for the symmetric stress tensor, are integrated in time (Refs. 3 and 4). The integration is carried out into the middle of the fourth rotation of the gear, when the vibrations have substantially attenuated and the equilibrium stress state is approximately attained. This computed solution, referred to as the true solution, is obtained for radial, tangential and shear stresses all over the gear. With this computed solution, the locations of the radial and tangential stress extrema are known, as shown in Fig. 2(a-b). We thus train our machine learning optimization algorithm on the stress and position data around these locations as well as define an optimal sensor layout over the gear for damage detection.

[2] U.S. patent application filed



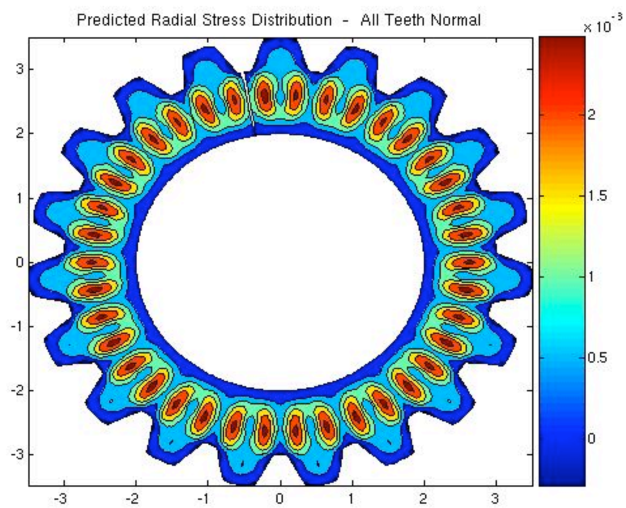
(a)



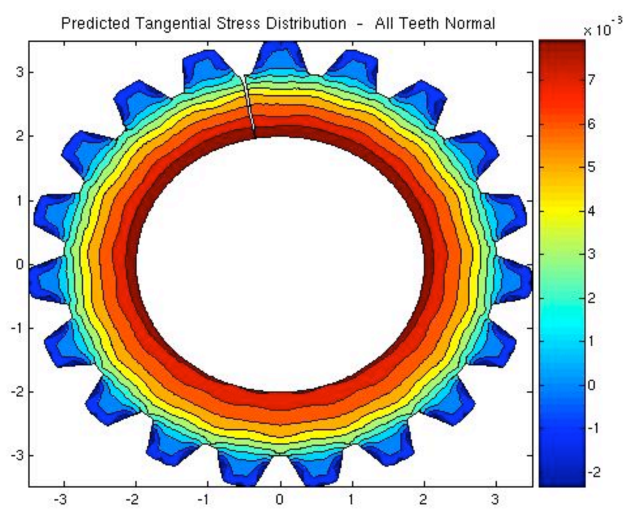
(b)

Fig. 2 True stress distribution; (a) radial stress (b) tangential stress

Using this strategy, we train the algorithm on about 10% of these data. A prediction of normal radial stress all over the gear is shown in Fig. 3.(a). Comparing Figs. 2(a) and 3(a), it is shown that the prediction follows the true solution closely. The rms error over the entire grid is about 5% . Fig. 3(b) shows the predicted normal tangential stress distribution. Again, comparison of Fig. 3(b) with Fig. 2(b) shows that the predicted and true tangential stresses are in close agreement. Extending the learning models thus constructed to test damage data, with one gear tooth made less rigid than the rest of the teeth, predictions of radial stress are made by the thus learned model. These predictions are shown in Fig. 4(a) as the difference between the true normal radial stress and the just predicted damage radial stress distributions. Inspection of Fig. 4(a) clearly shows a discrepancy in the radial stress distribution in a given region, and this local region turns out to be correspondent to be the damaged tooth. Same observation is made on inspection of Fig. 4(b) with respect to the tangential stress distribution.



(a)

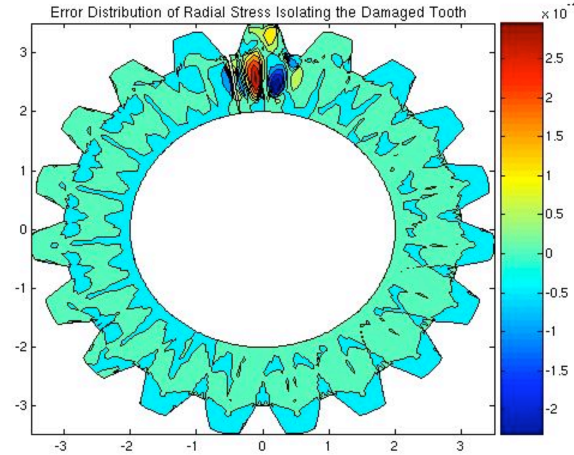


(b)

Fig. 3 Normal radial stress distribution over the gear ; (a) radial stress (b) tangential stress

Figs. 5(a-b) show the line plots of the error in radial and tangential stress distributions, respectively. The abscissa denotes the grid point index; the first 420 grid points represent the first tooth; the last 420 grid points represent the nineteenth tooth. The damage is clearly predicted around the first and the 19th teeth.

Finally, Fig. 6 shows the shear stress error distribution identifying the damaged tooth.



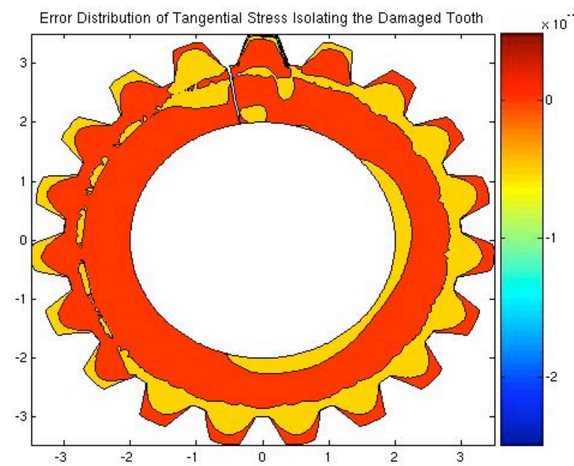
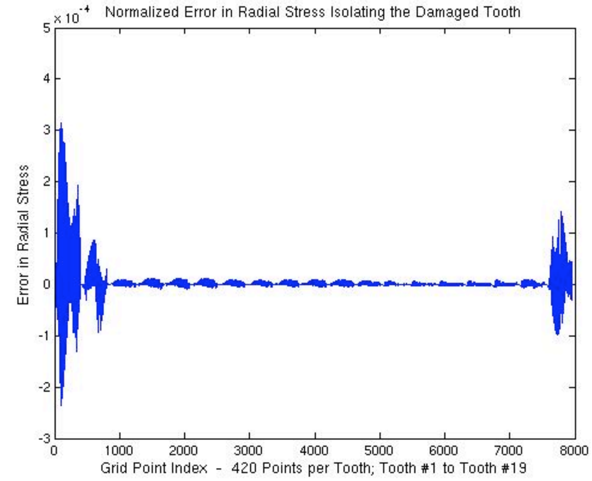
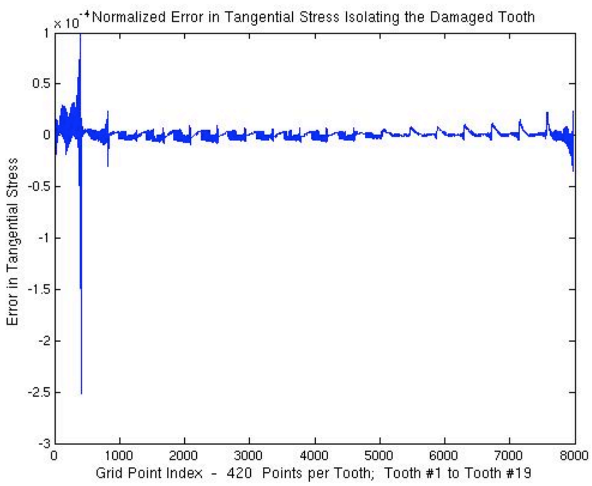


Fig. 4 Normalized error in stress distribution over the gear; (a) radial stress (b) tangential stress

This study thus establishes that for structural health monitoring, physics-based modeling and simulation is required to provide nominal solutions, both normal and damage, as reference solutions, which can then be used to train machine learning algorithms to subsequently test the incoming sensor data over a distributed network of sensors to detect damage. The first-principles modeling and simulation can also be used to guide an optimal placement of sensors over a given structural system..



(a)



(b)

Fig. 5 Normalized error in stresses isolating the damaged tooth; (a) radial stress (b) tangential stress

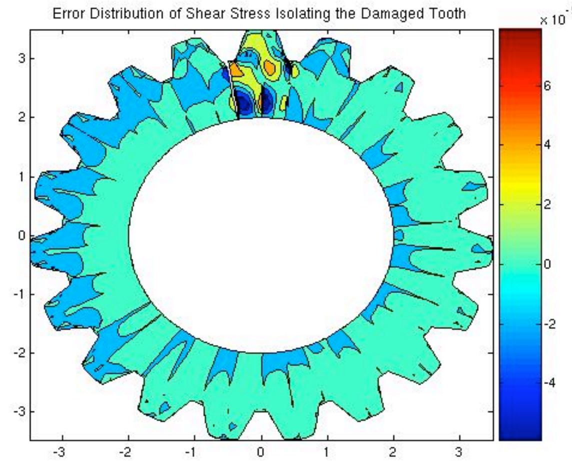


Fig. 6 Normalized error in shear stress distribution over the gear;

CONCLUSION

The multi-function optimization methodology developed in this study can be used to detect damage in any given structure for structural health monitoring. The methodology also holds promise for applicability in detecting an evolving damage such as crack propagation. The multi-disciplinary approach adopted here will first provide a large space of reference solutions or signatures corresponding to a variety of damage solutions, both stationary and dynamic, through the physics-based deterministic solutions. Then, these reference solutions will be used by the multi-function optimization technique used here to construct machine learning models to detect damage. This methodology can be used on a variety of platforms such as in space, aerospace and automotive structural applications, among others.

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ACKNOWLEDGMENTS

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